Bowling Leagues and Facebook Friends: Rethinking Social Capital in the Digital Age

Andrew J. Van Leuven[a,*], Trey Malone[b]

[a]Dept. of Community Development and Applied Economics, University of Vermont, Burlington, VT, USA
[b]Dept. of Agricultural Economics, Purdue University, West Lafayette, IN, USA

Abstract

This paper compares the "bowling alone" method of quantifying social capital—based on the density of civic organizations and brick-and-mortar institutions—with newer approaches that draw on billions of online friendship ties to assess economic connectedness and social cohesion. Using county-level data from across the continental United States, we construct and compare indices of traditional and digital social capital, mapping their geographic distributions and assessing their correlation. Our analysis reveals that these two measures are only weakly correlated and exhibit strikingly different spatial patterns, with traditional social capital highest in rural areas and digital social capital concentrated in metropolitan regions. Each measure captures complementary, but not substitutable, dimensions of community connectedness. These results challenge the idea that either metric alone is sufficient for transformative community development, stressing the importance of an integrated approach to understanding the full spectrum of local social ties in the modern era.

Keywords: *social capital, community development, social network, local institutions*

JEL codes: R11, Z13, C81

1. Introduction

American social capital has frayed, or so goes the conventional academic wisdom since at least the publication of *Bowling Alone* (Putnam, 2000). While the conventional wisdom is consistent, measuring this newly fractured civil society remains open for debate. Fraternal organizations, religious congregations, and neighborhood associations no longer anchor community life as they once did. In their place, looser, more distributed networks often facilitated by digital platforms have taken root. This transformation is especially salient for regional development, where embedded social networks are critical in shaping economic opportunity and institutional trust (Glaeser et al., 2004; Rahe et al., 2025).

Despite broad agreement that the nature of social connections has evolved, a persistent puzzle in the literature is how to meaningfully measure local connectedness in a way that reflects its changing structure and function. Traditional indicators of social capital are increasingly misaligned with modern social life, so simply counting organizational membership or voter turnout can misrepresent social cohesiveness (Claridge, 2018). At the same time, new forms of digital engagement generate rich but noisy social networks. It should come as no surprise that this mismatch limits our ability to assess the role of social networks in community economic outcomes, particularly in light of growing geographic disparities in economic opportunity and civic engagement (Woodhouse, 2006).

Social capital research has been criticized for creating "more smoke than light" (Halstead et al., 2022). How different are these measures of social networks? And how big are the implications of these differences as they relate to economic outcomes? To address these foundational questions, we compare traditional institutional measures of social capital with emerging digital network-based approaches in

*Corresponding author, andrew.vanleuven@uvm.edu

U.S. counties. We contrast the established "bowling alone" methodology (i.e., the notion that social capital can be measured by the density of local civic institutions, voter participation, and organizational membership) with recent innovations in social network analysis that leverage billions of social media connections to measure social cohesion at a high geographic resolution.

Our key contribution is to provide the first large-scale empirical comparison of traditional and digital approaches to measuring social capital, offering both methodological insights and substantive findings about the evolving nature of community connectedness in America. We find that while traditional and digital measures of social capital are only weakly correlated at the county level, they display markedly different spatial patterns and associations with economic outcomes. In addition to estimating the statistical correlation between contrasting measures of social capital, we also map the geographic distribution of both traditional and digital social capital measures to identify temporal trends and spatial patterns (especially urban-rural disparities). Traditional social capital is highest in rural and nonmetropolitan counties, while digital social capital is concentrated in metropolitan and coastal areas.

Perhaps most importantly for the community development literature, we evaluate the predictive validity of each measurement approach by testing its relationship with county-level economic outcomes such as population growth, income changes, and employment trends. Regression analyses reveal that the two measures have opposing relationships with economic growth, confirming that they capture complementary, rather than substitutable, dimensions of community connectedness. By comparing these approaches, we demonstrate that relying on a single metric risks overlooking critical forms of social capital that shape divergent community trajectories.

2. Background

2.1. Community Social Capital

The term *capital* has traditionally been defined as either the value of financial assets or a "store of some positive or advantageous quality" (Oxford University Press, 2025). As such, *social capital* refers to the assets that accrue from strong interpersonal relationships held by individuals or organizations (Bourdieu, 1980; Woolcock, 1998). These relationships breed trust and facilitate coordination and cooperation, allowing communities to function more effectively (Putnam, 1993).

Although pioneered by sociologists and political scientists, the concept of social capital has since gained wide attention in the social sciences, with high interest of those exploring economic growth (Farris et al., 2019; Robison et al., 2020a,b; Moreno and Malone, 2021). Regional economists and community development scholars draw on it to explain variations in economic prosperity and resilience across regions, recognizing that social bonds and networks help "shape local economies" (Blair and Carroll, 2016) by facilitating information flows, lowering transaction costs (Oh et al., 2014), and allowing the collective action required for economic coordination (Rahe et al., 2025). As Coleman (1988) observed, social capital enables the "achievement of certain ends that would not be attainable in its absence."

Recognizing its fundamental role in economic coordination, a growing body of research has examined how social capital drives local economic development and growth. This work largely finds that social capital can act as a catalyst for economic growth and regional development (Iyer et al., 2005; Westlund and Adam, 2010), particularly by influencing entrepreneurship and business formation (Kwon et al., 2013). Community-based social networks provide prospective entrepreneurs with essential business knowledge and offer signals regarding the viability of new ventures (Roxas and Azmat, 2014). By extension, social capital features prominently in the "community capitals" framework developed by Emery and Flora (2006), recognizing the role it plays in contributing to revitalization and entrepreneurship.

That said, prior studies have emphasized that the relationship between social capital and economic outcomes is more nuanced than a simple positive causal connection. Researchers have found instances where social capital does not significantly influence aggregate measures of output and employment (Casey and Christ, 2005; Baycan and Öner, 2023), and in some cases can be deleterious to economic growth (Portes and Landolt, 1996; Taylor et al., 2025). Moreover, social capital is not always a reliable community development asset, as some places have "deep social cleavages" that prove counterproductive to community development goals (Bridger and Alter, 2006). Communities sometimes cooperate and sometimes compete, making careful measurement of social capital of utmost importance, as its forms, functions, and effects can vary widely across communities and contexts (Westlund and Bolton, 2003).

2.2. Approaches to Measuring Social Capital

Early research on social capital quantified a given location's presence and influence of social capital via extensive primary data from ethnographic case studies, focus groups, and surveys (Putnam, 1993; Uzzi, 1999; Harpham et al., 2002). The field has since shifted toward *systematic* measurement at the community level, requiring consistently available data that can be compared across broader geographic areas. Researchers have typically operationalized social capital using traditional institutional indicators such as organizational membership, civic participation, and the density of community institutions like churches and bowling alleys (Putnam, 2000; Kyne and Aldrich, 2020; Vâlsan et al., 2023). These measures draw on consistently available data sources, including census records, election data, association directories, and business registries. A prominent example of this approach is the comprehensive county-level index developed by Rupasingha et al. (2006), which has been widely used by economists and policymakers as a robust proxy for regional social capital.

While historically valuable, traditional institutional measures of social capital face significant limitations in capturing the evolving nature of contemporary social connection. These metrics (e.g., organizational membership, voter turnout, and civic participation) suffer from temporal misalignment with modern social life, declining response rates in surveys, and institutional biases that may overemphasize formal over informal networks (Claridge, 2018; Coffé and Geys, 2007). Moreover, traditional approaches often struggle with differential measurement validity across urban and rural contexts, potentially missing the distributed, less institutionalized networks that increasingly characterize social organization (Stern and Dillman, 2006; Pénard and Poussing, 2010).

In response to these limitations, researchers have developed digital network-based approaches that leverage the unprecedented scale and granularity of social media data to map social connections. The Facebook Social Connectedness Index and similar measures analyze billions of friendship links to quantify the probability that individuals in different geographic areas are connected, creating high-resolution maps of social networks that update in real-time (Bailey et al., 2018; Kuchler et al., 2022). These digital measures can offer substantial advantages over traditional approaches: they capture actual social connections rather than institutional proxies, provide geographic granularity down to ZIP code and county levels, reflect contemporary forms of social interaction, and generate longitudinal data that can track changes in network structure over time (Chetty et al., 2022b).

Despite their analytical promise, digital measures of social capital also face important limitations. Selection bias represents a fundamental concern, potentially excluding populations whose social capital may be most relevant for community development outcomes. Additionally, questions remain about whether digital connections reflect "real" social capital in the sense of trust, reciprocity, and collective efficacy that traditional theories emphasize, or whether they capture a different, perhaps shallower form of social connection unique to the internet.

2.3. Motivation and Research Questions

This study addresses these challenges by conducting a large-scale empirical comparison of traditional institutional measures of social capital with emerging digital network-based approaches across all continental U.S. counties. Despite the widespread adoption of both measurement strategies, no systematic evaluation has examined whether they capture the same underlying social phenomena or yield fundamentally different insights about community connectedness. This empirical gap leaves scholars uncertain about the validity of their theoretical claims and policymakers unsure which measurement tools accurately identify the social assets that drive community development outcomes.

Measurement uncertainty can have a profound impact on policy-relevant debates. If traditional and digital measures of social capital behave in fundamentally distinct ways, then unique dimensions of social organization may have divergent effects on community outcomes. Relying on measurement approaches that misidentify where social capital exists risks misdirecting resources toward communities that appear disconnected by traditional metrics but are actually well-networked through digital channels, while leaving truly isolated places unrecognized and underserved. Indeed, misguided rural development programs, entrepreneurship initiatives, and place-based economic development strategies might lead to unintended consequences or no effect on community social assets at all.

Three research questions guide this analysis:

1. How does county-level social capital differ over time and across state and rural-urban boundaries? Do indicators such as local civic organizations, associational establishments, and community engagement move together? Do new approaches to measuring *digital* social capital vary geographically, such as Facebook network analysis?

2. To what extent are social capital measures based on county-level institutional and organizational data statistically correlated with those derived from online social network data?

3. Which measure of social capital (i.e., county-level institutional data or online social network data) better explains regional economic outcomes such as population growth, income changes, and employment trends?

3. Data

To address these questions, we constructed two separate indices, each measuring different aspects of county-level social capital. The first index is a replication of the index developed by Rupasingha et al. (2006), which used data from a variety of sources to create a comprehensive measure of traditional social capital encompassing four key dimensions (see Table 1). These components were combined to generate a single social capital index that captures the breadth of formal civic institutions and participatory behaviors that anchor community life.

We borrowed this approach to create a similar social capital index for three time periods: 2002, 2012, and 2022.[1] Rather than relying solely on County Business Patterns data, we employed the National Establishment Time Series (NETS) database, which provides more comprehensive coverage of geolocated business establishments across all sectors and establishment sizes (Walls, 2022). This substitution is particularly important for capturing smaller civic organizations and establishments that may be underrepresented in traditional federal business registries. Voter turnout data were obtained from MIT Election Data and Science Lab (2018) and normalized using the U.S. Census Bureau's Citizen Voting Age Population (CVAP) estimates for the 2000, 2012, and 2020 presidential elections to ensure consistent denominators across time periods. Census response rates and non-profit organization counts were obtained from their respective original sources and updated to reflect the most recent available data for each time period. We followed the approach of Rupasingha et al. (2006) by standardizing the four factors as z-scores and conducting a principal component analysis. The first principal component was then used as our "traditional social capital" (TSC) index.

The second index drew upon data from the "Opportunity Atlas" public repository (Chetty et al., 2022b). Given that this dataset was constructed using proprietary data, we made no attempts to replicate or modify the original methodology, including the addition of supplementary time periods for temporal analysis. From the county-level measures available in Chetty et al. (2022a), we selected three primary variables: economic connectedness, social cohesiveness, and civic engagement, which are roughly summarized in Table 2. As with our construction of the TSC index, we standardized each measure, conducted principal component analysis, and used the first principal component as our "digital social capital" (DSC) index.

With both indices constructed, we collected additional variables to serve as outcome measures and controls for ordinary least squares (OLS) regression analyses examining the relationship between TSC/DSC (traditional and digital social capital indices) and three indicators of community economic vitality: population growth, income growth, and employment growth. These outcome variables were derived from the Bureau of Economic Analysis (BEA) county profile data and were calculated as annualized growth rates over comparable time periods to ensure temporal alignment with our social capital measures. Control variables included standard demographic and economic characteristics such as population density, educational attainment, industry composition, and geographic region to iso-

[1] When data were unavailable for the target years, we used the nearest available year: 2000 Census data for the 2002 index, 2012 American Community Survey for the 2012 index, and 2020 presidential election results for the 2022 index.

Table 1: *Traditional Social Capital Index Components*

Dimension	Description (from Rupasingha et al., 2006)	Source	
		Rupasingha Study	*This Study*
Associational Density	Number of civic, religious, business, political, professional, labor, and recreational establishments per capita	County Business Patterns	NETS (Walls, 2022)
Electoral Participation	Voter turnout in presidential elections (percentage of eligible voters)	Leip's Atlas of U.S. Presidential Elections	MIT Election Data and Science Lab (2018)
Civic Engagement	County-level response rates to the U.S. Census (percentage responding)	U.S. Census	U.S. Census (compiled by Kiper, 2020)
Nonprofit Capacity	Density of tax-exempt organizations excluding those with international scope	National Center for Charitable Statistics	Urban Institute (2025) NCCS Data Catalog

Table 2: *Digital Social Capital Index Components*

Dimension	Description (from Chetty et al., 2022b)
Economic Connectedness	How often people from different income levels are friends with each other on Facebook (essentially whether rich and poor residents know each other personally)
Social Cohesiveness	How tightly knit local social networks are, based on whether friends also know each other and whether people's friendships stay within the county rather than spanning long distances
Civic Engagement	How actively residents participate in community groups and causes online, measured through Facebook volunteering groups and local civic organization pages

late the independent effects of social capital on economic outcomes while accounting for potential confounding factors.

4. Methods

4.1. Exploratory Analysis: Social Capital Across Time and Geography

Our modified TSC index was constructed using an identical data structure and methodology across three time periods (2002, 2012, and 2022), allowing for a direct comparison of social capital trends over time. We conduct an analysis of variance (ANOVA) to test whether mean TSC values differ significantly across these periods. Rather than representing entire decades, each year serves as a point-in-time snapshot, which we treat as a discrete cross-sectional comparison rather than a continuous time series.

To assess regional heterogeneity in social capital patterns, we calculate mean TSC values for each of the nine U.S. Census divisions across all three time periods and examine absolute differences over the 20-year study period to identify regions experiencing differential trajectories in traditional social capital. Similarly, we examine urban-rural disparities by calculating separate TSC trends for metropolitan and nonmetropolitan counties using the USDA Economic Research Service's rural-urban continuum codes, with particular attention to how TSC varies across the full spectrum of rural-urban classifications.

We then use choropleth maps to visualize the geographic distribution of both social capital measures. For TSC, we present county-level maps for all three time periods (2002, 2012, 2022) to illustrate spatial shifts over time. The DSC measure, available only for 2022, is mapped separately to display contemporary digital social capital patterns. Maps use quintile-based classification schemes to highlight relative differences across counties, allowing direct visual comparison of the spatial distributions of traditional versus digital social capital measures.

4.2. Correlation Analysis: Traditional versus Digital Social Capital

We assess the statistical relationship between TSC and DSC using Pearson product-moment correlation coefficients (Pearson's r), focusing on 2022 data when both measures are available. The global correlation provides an overall measure of association between traditional institutional approaches and digital network-based approaches to measuring social capital.

To examine contextual variation in this relationship, we conduct stratified correlation analyses across multiple dimensions. We calculate separate correlations for each of the nine U.S. Census regions to identify geographic variation in TSC-DSC relationships. We also examine differences along the urban-rural continuum by computing separate correlations for metropolitan and nonmetropolitan counties using CBSA classifications. We supplement correlation analysis with bivariate scatterplots to identify potential outliers and assess linearity assumptions.

To quantify spatial autocorrelation (i.e., clustering) patterns, we calculate Moran's I spatial autocorrelation statistics for TSC and DSC measures (both in 2022) and employ Getis-Ord $Gi*$ hotspot analysis to identify statistically significant clusters of high and low social capital values. The Moran's I analysis identifies whether counties with similar social capital levels tend to cluster geographically, while the Getis-Ord hotspot mapping reveals the specific locations of these clusters, distinguishing between "hot spots" (areas of concentrated high values) and "cold spots" (areas of concentrated low values).

4.3. Regression Analysis: Social Capital and Economic Outcomes

Finally, we employ a set of basic ordinary least squares (OLS) regressions to assess the relationship between social capital measures and three indicators of regional economic vitality: population growth, income growth, and employment growth. All outcome variables are calculated as annualized percentage change rates over the period 2017-2022 to ensure temporal alignment with our 2022 social capital measures. This combination of outcome variables follows established approaches in regional development literature, particularly building on the framework developed by Carlino and Mills (1987) for analyzing determinants of county-level growth (see also Deller and Lledo, 2007). We anticipate that traditional and digital measures of social capital may exhibit differential relationships with each outcome, as different forms of social capital may facilitate distinct pathways to economic development.

Our empirical strategy involves estimating three sets of models for each outcome variable:

$$Y_i = \alpha + \beta_1 \text{TSC}_i + \delta \mathbf{X}_i + \epsilon_i \quad (1)$$
$$Y_i = \alpha + \beta_2 \text{DSC}_i + \delta \mathbf{X}_i + \epsilon_i \quad (2)$$
$$Y_i = \alpha + \beta_1 \text{TSC}_i + \beta_2 \text{DSC}_i + \delta \mathbf{X}_i + \epsilon_i \quad (3)$$

where Y_i represents the economic outcome for county i, $\mathbf{X}_i$ is a vector of control variables, and ϵ_i is the error term. The separate estimation of equations (1) and (2) allows direct comparison of each social capital measure's explanatory power, while equation (3) tests whether the measures capture complementary aspects of social capital when included simultaneously. Control variables include standard demographic and economic characteristics: population density (log), age dependency ratio, percentage with bachelor's degree or higher, unemployment rate, industry diversity (Herfindahl index), and census region fixed effects. These controls account for observable confounders that might bias the relationship between social capital and economic outcomes.

We use adjusted R-squared values and the Akaike Information Criterion (AIC) to assess model performance. We also include checks for heteroskedasticity and multicollinearity (variance inflation factors). However, we acknowledge that these OLS models are not causal and are likely biased due to unobserved heterogeneity and potential reverse causality between social capital and economic outcomes. However, we include this multivariate analysis because of its value in establishing baseline associations and comparing the relative predictive power of traditional versus digital social capital measures within a controlled framework. While the results should be interpreted with caution, as they represent correlational rather than causal relationships, they nonetheless demonstrate how differing measurement approaches might misspecify how unique aspects of social capital are correlated to economic vitality.

5. Results

5.1. Exploratory Results

Descriptive statistics (see Table 3) reveal a definitive upward trend in the Traditional Social Capital (TSC) index over the 20-year study period.[2] While

[2]We did not calculate each year's TSC index in isolation, as this would impose identical means and standard deviations

the absolute values of PCA-derived scores are not directly interpretable, the relative change is substantial: the average U.S. county scored nearly one full point higher on the TSC scale in 2022 compared to two decades prior, representing a consistent strengthening of traditional social capital measures over time. The ANOVA results confirm that these temporal differences are highly statistically significant, indicating a genuine change in social capital patterns across American counties over the two-decade period.

Further descriptive statistics (see Table 4) emphasize substantial heterogeneity in both TSC and DSC by region and across the rural-urban divide. In the top section of the table, the West North Central and New England divisions stand out for having the highest levels of observed TSC, while the East South Central and West South Central divisions report the lowest levels.[3] When comparing metropolitan and nonmetropolitan counties, nonmetropolitan areas consistently demonstrate higher TSC, highlighting a persistent rural advantage in traditional social capital.[4]

The middle section of the table summarizes changes in TSC from 2002 to 2022. As the TSC index is a standardized, unitless measure not anchored to real-world quantities, we report absolute differences rather than percent change, as the latter would be difficult to interpret meaningfully. Across all regions and county types, average TSC increased over the study period, confirming a nationwide upward trend. The South Atlantic and Middle Atlantic divisions showed the strongest growth during this time, while New England and the two North Central divisions experienced the most modest growth (a pattern likely reflecting the fact that these regions already had relatively high levels of TSC at the outset). Metropolitan counties outpaced nonmetropolitan counties in average gains, albeit by a small margin.

The bottom section of Table 4 highlights stark differences in the geographic distribution of digital social capital (DSC) relative to traditional measures. At the regional level, rankings for DSC generally mirror those for TSC: regions such as New England rank high on both, while regions like the East South Central rank low. However, this alignment breaks down when differentiating between rural and urban areas. In contrast to TSC, which is consistently higher in nonmetropolitan areas, DSC is significantly higher in *metropolitan* counties. This reversal suggests that while rural communities retain strengths in traditional civic institutions, urban areas have developed greater digital connectivity and online engagement. These contrasting patterns reinforce the earlier finding that traditional and digital social capital represent distinct forms of social organization with different spatial distributions across the American landscape.

Figure 1 visually elaborates on rural-urban differences in TSC and its evolution over the two-decade study period. Each RUCC category is depicted with three bars, representing TSC levels in 2002, 2012, and 2022; the figure demonstrates a monotonic increase in TSC over time across all rural-urban classifications, reinforcing the broad upward trend reported in Table 3. Again, while the index measures are not directly interpretable, the relative differences between county types nonetheless illustrate clear patterns: the most rural counties (RUCC codes 8 and 9) consistently exhibit the highest TSC levels, with their advantage widening substantially over time.

The figure reveals a heterogeneous rural-urban gradient, emphasizing the uniqueness of community-specific social capital. While the most urban counties (RUCC codes 1-3) start below the mean in 2002, they maintain relatively stable positions through 2022. Notably, mid-tier counties (RUCC codes 4-7) actually performed worse than the most urban areas in both 2012 and 2022, suggesting that traditional social capital may be weakest in these intermediate communities rather than in the largest metropolitan areas. This U-shaped pattern highlights that the rural advantage in traditional social capital is most pronounced at the extremes of the rural-urban continuum, with the greatest gains occurring in the most rural counties over the past two decades.

on all years. Instead, we standardized all components using 2002 values as the baseline before running PCA on the pooled dataset, allowing for meaningful comparisons over time.

[3]See Figure 3 for a labeled map of census divisions.

[4]Metropolitan status was determined using the USDA Economic Research Service's rural-urban continuum (RUCC) codes. Counties with a RUCC $\leq$ 3 were considered metropolitan, while all others were labeled nonmetropolitan.

Table 3: *Descriptive Statistics for Traditional Social Capital Index by Time Period*

	Mean	Std Dev	Min	Max	N
2002 TSC	-0.55	1.25	-5.35	14.55	3,018
2012 TSC	0.16	1.47	-4.74	19.95	3,045
2022 TSC	0.39	1.44	-2.92	36.54	3,046

ANOVA Results: $F(2, 9106) = 378.7$, $p < 0.001$

Table 4: *Summary of Traditional & Digital Social Capital by Census Division and Metropolitan Status*

Division	Mean	Std. Dev.	Min	Max
TSC Measure, 2022				
East North Central	0.21	0.68	-2.61	3.70
East South Central	-0.40	0.77	-2.62	2.75
Middle Atlantic	0.36	0.76	-2.02	3.85
Mountain	0.89	1.82	-2.92	10.62
New England	0.99	0.96	-0.48	4.13
Pacific	0.66	1.30	-2.27	5.63
South Atlantic	0.32	0.94	-2.52	4.69
West North Central	1.19	1.39	-2.71	15.93
West South Central	-0.25	2.13	-2.83	36.54
Metropolitan Counties	0.13	0.94	-2.83	4.4
Nonmetropolitan Counties	0.55	1.66	-2.92	36.54
TSC Measure, Change 2002–2022				
East North Central	+0.64	+0.4	-1.19	+1.99
East South Central	+0.94	+0.5	-1.23	+2.78
Middle Atlantic	+1.13	+0.57	-0.94	+2.15
Mountain	+0.77	+0.95	-3.57	+5.5
New England	+0.6	+0.5	-0.86	+2.4
Pacific	+0.83	+0.59	-2.33	+2.16
South Atlantic	+1.56	+0.59	-0.51	+3.48
West North Central	+0.67	+0.69	-1.74	+3.17
West South Central	+0.8	+1.71	-1.76	+33.72
Metropolitan Counties	+1.03	+0.62	-1.43	+3.49
Nonmetropolitan Counties	+0.86	+1.09	-3.57	+33.72
DSC Measure, 2022				
East North Central	0.32	0.83	-2.53	3.53
East South Central	-1.18	1.19	-5.08	3.02
Middle Atlantic	0.3	0.83	-1.55	4.02
Mountain	0.76	1.46	-2.64	8.99
New England	0.95	0.98	-1.28	3.4
Pacific	0.83	1.11	-1.62	4.4
South Atlantic	-0.58	1.49	-4.14	6.73
West North Central	0.61	0.97	-3.68	3.61
West South Central	-0.42	1.15	-4.87	2.93
Metropolitan Counties	0.44	1.24	-3.87	8.99
Nonmetropolitan Counties	-0.3	1.32	-5.08	4.33

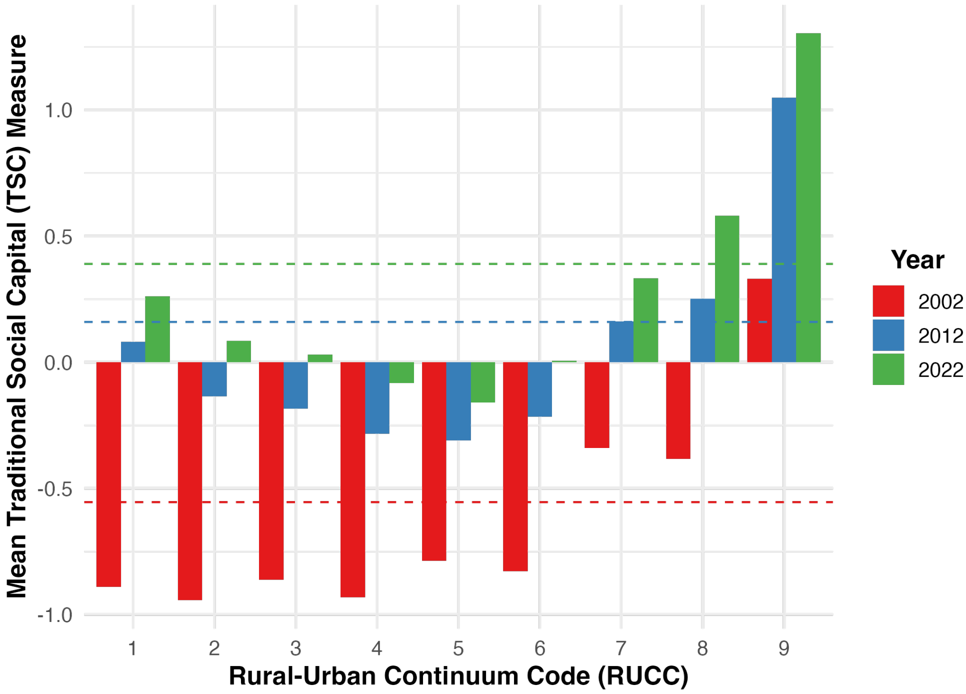


Figure 1: *Mean TSC Measure by RUCC and Year*

The maps in Figure 2 use quintile groupings rather than absolute units of measure. Because the quintiles are recalculated for each year, a county remaining in the same color does not necessarily mean its absolute TSC level remained unchanged; rather, the maps illustrate how counties rank relative to one another in each period. Maps with green shading illustrate the spatial distribution of TSC in 2002, 2012, and 2022, while the map with blue shading illustrates the spatial distribution of DSC in 2022.

At first glance, the broad regional patterns in TSC depicted by Figure 2 appear stable, with counties in the North Central divisions and New England consistently occupying the top quintile. However, a closer look reveals notable shifts in the national distribution of social capital. Over time, many counties along the Gulf and Atlantic coasts move into higher quintiles, particularly in the Carolinas, Georgia, and parts of Alabama, Mississippi, and Louisiana. Modest improvements are also evident in parts of the Southwest, including Arizona and New Mexico. In contrast, some areas of the upper Midwest (particularly in Wisconsin and Michigan) are projected to drop into lower quintiles by 2022. These findings reaffirm the earlier statistical results, which showed regional heterogeneity and temporal change, and they demonstrate that the spatial allocation of social capital is dynamic, with regions rising and falling in relative standing over the two-decade period.

While the previous tables and figures have focused primarily on traditional social capital (TSC) due to the limited availability of digital social capital (DSC) for only a single period, the bottom two panes of Figure 2 provide a compelling side-by-side comparison of both measures in 2022. The contrast between the two maps demonstrates that TSC and DSC exhibit markedly different spatial distributions that appear almost complementary. Many counties with high TSC are concentrated in the upper Midwest, Great Plains, and northern New England, and tend to score lower on DSC. By contrast, areas with strong DSC concentrations are more prevalent in urbanized regions, particularly along the coasts and metropolitan areas. This relationship suggests that traditional and digital forms of social capital represent distinct, geographically differentiated modes of civic engagement, with rural areas maintaining a stronger presence in conven-

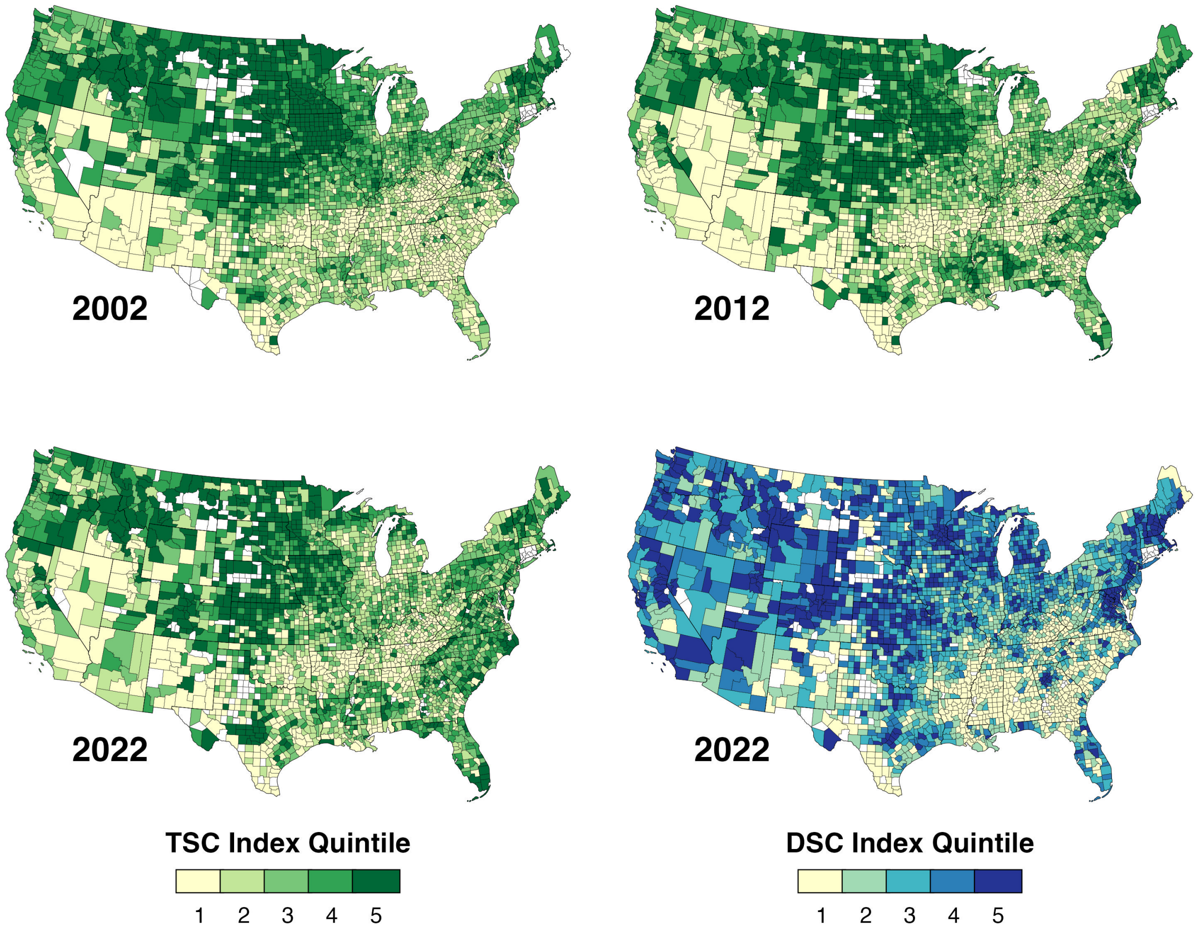


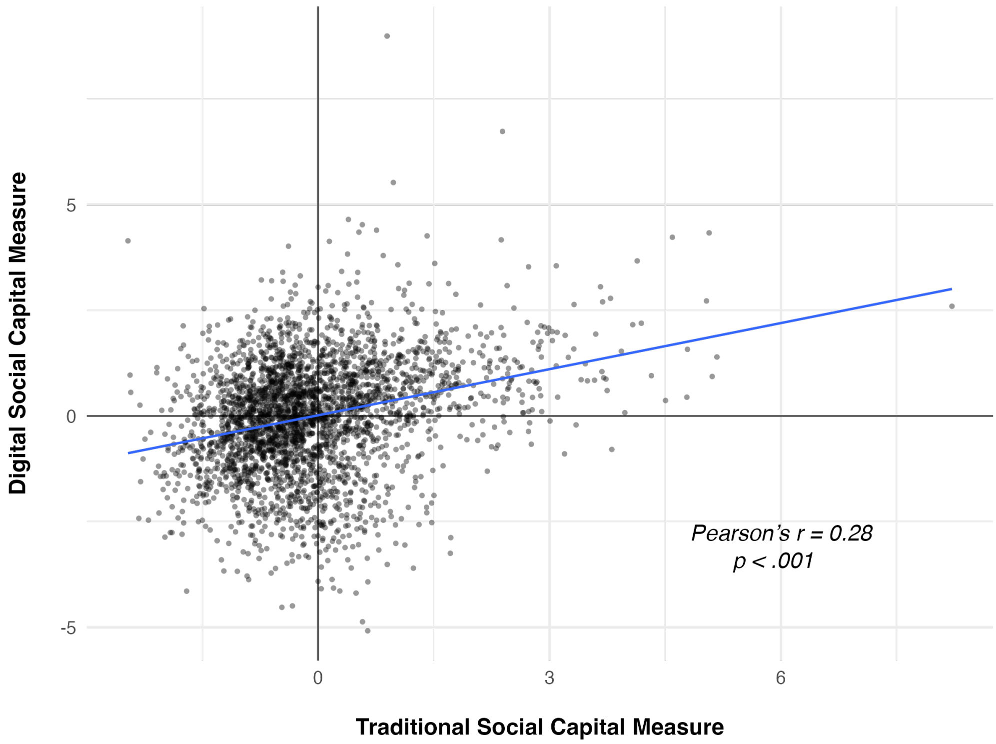
Figure 2: *County-Level TSC in 2002, 2012, and 2022; County-Level DSC in 2022*

tional social institutions. In contrast, urban areas develop robust digital networks and engage in online civic participation. These spatial patterns raise important questions about the relationship between TSC and DSC, as well as their connection to other county-level characteristics, motivating a closer examination through correlation analysis.

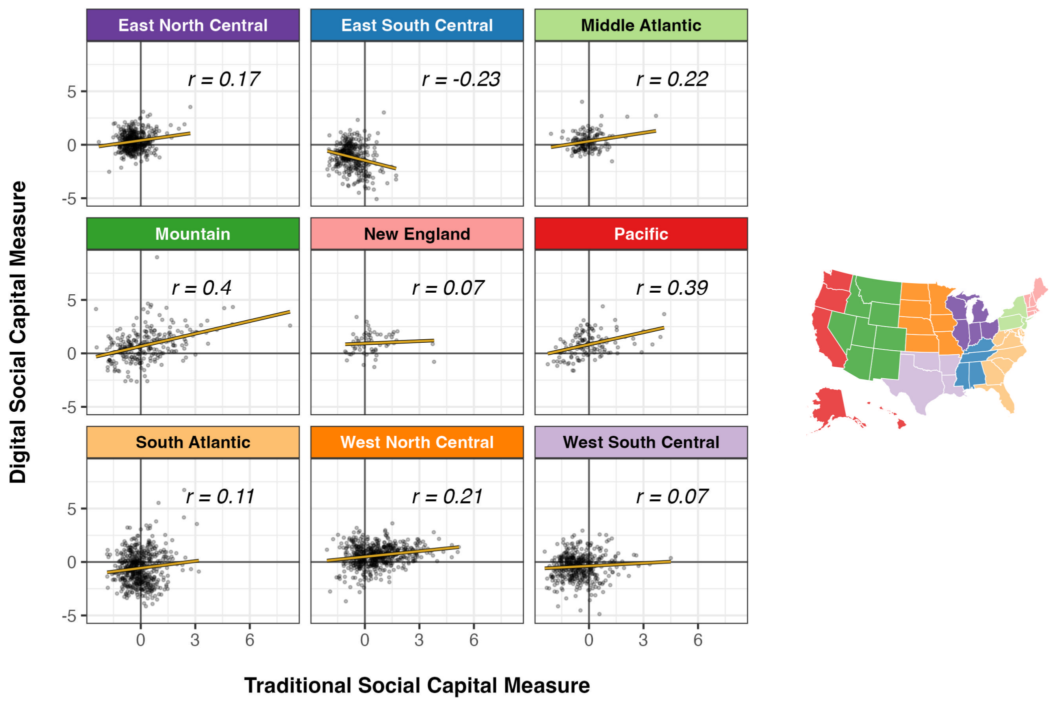
5.2. Correlation Results

Our core contribution is a systematic comparison of traditional and digital measures of social capital. Panels (a) and (b) of Figure 3 display the correlation between these two measures at both the national and regional levels, respectively. As shown in the nationwide scatter plot, Pearson's r for the correlation between TSC and DSC is 0.28 ($p < 0.001$), indicating a statistically significant but weak relationship between the two measures.[5] This result suggests that traditional and digital social capital measures capture related but largely distinct aspects of community connectedness, with only 8% of the variance in one measure associated with the other. The moderate correlation suggests that these measurements do not capture the same underlying phenomenon, supporting our hypothesis that evolving forms of social organization necessitate new measurement approaches.

[5] A small number of counties (highlighted in Figure A1 of the appendix) stand out as notable outliers, exhibiting much higher or lower levels of digital or traditional social capital than would be predicted by the overall trend. These outliers may reflect unique local circumstances or measurement artifacts, but they do not substantially affect the overall correlation between the two measures.



(a) Nationwide



(b) By Census Division

Figure 3: *Scatterplots of 2022 Traditional & Digital Social Capital Measures*

Regional differences largely align with the nationwide finding, with only the Pacific census division having a larger correlation coefficient (0.39). Interestingly, in the East South Central division (Kentucky, Tennessee, Mississippi, and Alabama), TSC and DSC are *negatively* correlated ($r = -0.23$), meaning that counties with higher levels of traditional social capital are actually associated with lower levels of digital social capital. This inverse relationship suggests a potential substitution effect in this region, where strong traditional civic institutions may coincide with weaker digital networks, or that counties in this division represent distinct social capital "types" that rely primarily on either traditional *or* digital forms of connection but rarely both simultaneously.

The correlation between TSC and DSC also varies substantially along the urban-rural continuum, with metropolitan counties showing a weaker relationship ($r = 0.26$) compared to nonmetropolitan counties ($r = 0.42$). This pattern suggests that rural areas may exhibit more coherent social capital profiles, where traditional and digital measures tend to move in tandem, whereas urban areas display more complex, potentially fragmented social capital landscapes, where institutional and network-based measures operate more independently.

Beyond examining the statistical relationship between TSC and DSC measures, we also assessed whether each form of social capital exhibits spatial clustering patterns, i.e., whether counties with similar social capital levels tend to be geographically proximate. To do this, we first calculated a "global" (i.e., all counties included) measure of spatial autocorrelation, Moran's I, which detects the overall tendency for similar values to cluster together across the entirety of the 2,962 counties used in the analysis. This measure (see table in Figure 4) was roughly 0.43 for TSC and 0.6 for DSC, both strongly significant, suggesting that counties' levels of social capital are not spatially independent but tend to cluster geographically.

The maps in Figure 4 illustrate where spatial autocorrelation is strongest, highlighting clusters of counties with pronounced local similarity in social capital. The top two maps display the local $Gi*$ statistic for each county, which measures how strongly a county is surrounded by neighbors with similarly high or low social capital values; darker shading indicates stronger local clustering (Getis and Ord, 1992). The bottom two maps show only those counties where the $Gi*$ statistic is statistically significant, revealing "hot spots" (in red) and "cold spots" (in blue). These groups consisted of counties that were significantly surrounded by others with similarly high or low levels of social capital, respectively.

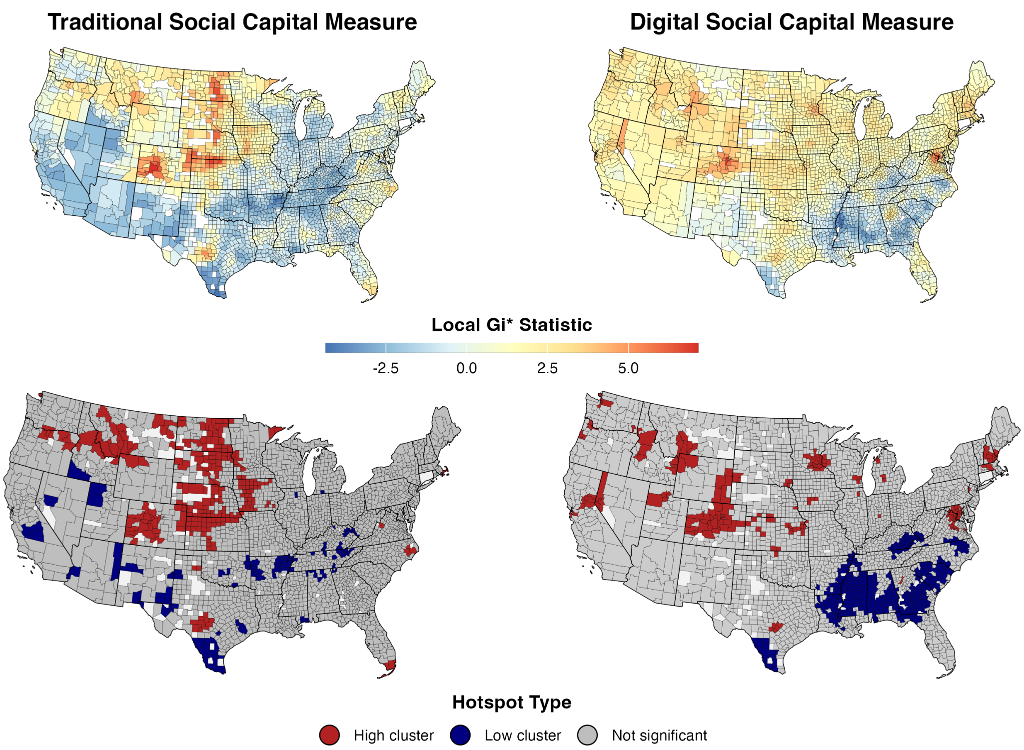
Comparing the hot and cold spots across traditional and digital measures reveals both convergence and divergence in spatial patterns. Some similarities emerge, with hotspots scattered along the Central Plains and Northern Rockies across both measures, as well as nearly identical cold spots at the southern tip of Texas. However, stark differences are also apparent, most notably a massive DSC cold spot spanning from Louisiana to South Carolina that is largely absent in the TSC map.[6] These spatial disparities reinforce the broader finding from the correlation analysis: traditional and digital social capital measures capture complementary rather than substitutable dimensions of community connectedness.

5.3. Regression Results

The final component of our analysis comprises a trio of descriptive regression models that examine the relationship between our two measures of social capital and three different regional economic outcomes. Tables 5 to 7 present the core OLS results examining the associations between social capital and employment growth, income growth, and population growth from 2017–2022. Across all three outcome variables, traditional social capital (TSC) and digital social capital (DSC) exhibit opposing patterns of association, suggesting these measures capture fundamentally different aspects of social organization and their economic implications.

The employment growth results in Table 5 demonstrate a clear divergence between the two social capital measures. Traditional social capital exhibits a significant negative association with employment growth, whereas digital social capital shows a significant positive association. When both measures are included simultaneously in Model 3, the coefficients remain virtually unchanged and highly signif-

[6] For reference, an additional map (see Figure B1, included in the appendix to conserve space) highlights the exact counties where there was "agreement" between the TSC and DSC hot/cold-spot maps.



Measure	TSC Measure	DSC Measure
Moran's I Statistic	0.4349	0.5981
Test Statistic	38.895	53.457
p-value	< 0.0001	< 0.0001

Figure 4: *Measures of Local and Global Spatial Autocorrelation*

icant, indicating that these relationships are robust and that the measures capture distinct phenomena rather than overlapping constructs. The combined model achieves the highest explanatory power (i.e., highest adjusted R^2 and lowest AIC), suggesting that both forms of social capital contribute unique information about employment dynamics.

With population growth as the outcome variable, Table 6 mirrors the previous results, but with an even more pronounced contrast between the two social capital measures. Traditional social capital exhibits a strong negative association with population growth, while digital social capital shows an equally strong positive association. The magnitude and opposing signs of these coefficients are particularly noteworthy, as they are nearly identical in absolute value. Of the three sets of regressions, the population growth models achieve the highest overall explanatory power (adjusted $R^2 = 0.403$ for the combined model), suggesting that social capital measures are particularly relevant for understanding demographic dynamics.

Finally, income growth patterns (Table 7) reveal an inverse relationship between the two social capital measures, contrasting with the results for employment and population change. Traditional social capital demonstrates a significant positive association with income growth, whereas digital social capital exhibits a significant negative relationship. Again, these coefficients remain stable when both measures are included together, reinforcing the independence of their effects. However, the explanatory power for income models is lower than that of employment and population models, perhaps reflecting the greater complexity of income determination processes at the county level.

Table 5: *Social Capital and Employment Change (2017–2022)*

	TSC Only	DSC Only	Both
	(1)	(2)	(3)
Traditional Social Capital (TSC)	-0.012^{***}		-0.012^{***}
	(0.002)		(0.002)
Digital Social Capital (DSC)		0.010^{***}	0.010^{***}
		(0.001)	(0.001)
Log Population Density	0.008^{***}	0.011^{***}	0.007^{***}
	(0.002)	(0.002)	(0.002)
Unemployment Rate	-0.006^{***}	-0.003^{**}	-0.004^{***}
	(0.001)	(0.001)	(0.001)
Age Dependency Ratio	0.225^{***}	0.159^{***}	0.205^{***}
	(0.018)	(0.017)	(0.018)
Bachelor's Degree or Higher	0.176^{***}	0.034	0.104^{***}
	(0.021)	(0.022)	(0.024)
Industry Diversity Index	0.00004	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)
Metropolitan County	0.032^{***}	0.031^{***}	0.028^{***}
	(0.003)	(0.003)	(0.003)
Observations	2,962	2,962	2,962
Adjusted R^2	0.284	0.284	0.295
AIC	-7571.0	-7569.6	-7614.6
Census Division FE	Yes	Yes	Yes

Note: *p<0.05; **p<0.01; ***p<0.001
Robust standard errors in parentheses.

Table 6: *Social Capital and Population Change (2017–2022)*

	TSC Only	DSC Only	Both
	(1)	(2)	(3)
Traditional Social Capital (TSC)	-0.015^{***}		-0.015^{***}
	(0.001)		(0.001)
Digital Social Capital (DSC)		0.016^{***}	0.016^{***}
		(0.001)	(0.001)
Log Population Density	0.001	0.004^{***}	0.0002
	(0.001)	(0.001)	(0.001)
Unemployment Rate	-0.009^{***}	-0.005^{***}	-0.006^{***}
	(0.001)	(0.001)	(0.001)
Age Dependency Ratio	0.225^{***}	0.132^{***}	0.192^{***}
	(0.012)	(0.011)	(0.012)
Bachelor's Degree or Higher	0.149^{***}	-0.061^{***}	0.034^{*}
	(0.014)	(0.014)	(0.015)
Industry Diversity Index	-0.0003^{***}	-0.0004^{***}	-0.0004^{***}
	(0.0001)	(0.0001)	(0.0001)
Metropolitan County	0.019^{***}	0.016^{***}	0.012^{***}
	(0.002)	(0.002)	(0.002)
Observations	2,962	2,962	2,962
Adjusted R^2	0.345	0.361	0.403
AIC	-9963.7	-10034.6	-10233.1
Census Division FE	Yes	Yes	Yes

Note: *p<0.05; **p<0.01; ***p<0.001
Robust standard errors in parentheses.

Table 7: *Social Capital and Income Change (2017–2022)*

	TSC Only	DSC Only	Both
	(1)	(2)	(3)
Traditional Social Capital (TSC)	0.014***		0.014***
	(0.002)		(0.002)
Digital Social Capital (DSC)		−0.009***	−0.009***
		(0.002)	(0.002)
Log Population Density	−0.001	−0.005*	−0.001
	(0.002)	(0.002)	(0.002)
Unemployment Rate	−0.004**	−0.006***	−0.005***
	(0.001)	(0.001)	(0.001)
Age Dependency Ratio	0.023	0.095***	0.041
	(0.023)	(0.022)	(0.023)
Bachelor's Degree or Higher	0.054*	0.201***	0.118***
	(0.027)	(0.027)	(0.030)
Industry Diversity Index	0.0004**	0.0005***	0.0004***
	(0.0001)	(0.0001)	(0.0001)
Metropolitan County	−0.001	−0.001	0.002
	(0.004)	(0.004)	(0.004)
Observations	2,962	2,962	2,962
Adjusted R^2	0.131	0.125	0.137
AIC	-6234.9	-6215.6	-6255.2
Census Division FE	Yes	Yes	Yes

Note: *p<0.05; **p<0.01; ***p<0.001
Robust standard errors in parentheses.

The control variables generally perform as expected across models, with a few notable exceptions. Higher education levels (bachelor's degree or higher) are consistently associated with positive economic outcomes, although the relationship varies in strength across different outcomes. Metropolitan counties show positive associations with employment and population growth, but mixed results for income growth. The robustness of our core social capital findings across different model specifications, combined with the consistent improvement in model fit when both measures are included, supports the interpretation that traditional and digital social capital capture complementary but distinct dimensions of social organization relevant to regional economic development.

As indicated in Figure 4, significant spatial autocorrelation is present in both county-level measures of social capital. Consequently, we conducted a Lagrange Multiplier test and applied the decision tree established by Anselin (1988) to determine that a Spatial Autoregressive Combined (SAC) model was the most appropriate specification to account for spatial dependence in our regression models.

As indicated by the Moran's I statistics mentioned above (see Figure 4), both measures of social capital exhibit significant spatial autocorrelation. To address this issue, we conducted Lagrange Multiplier tests and applied the decision framework outlined by Anselin (1988); the diagnostic statistics indicated the Spatial Autoregressive Combined (SAC) model as the most appropriate specification for accounting for spatial dependence.[7] These spatial models (Tables D1 to D3 in the appendix) generally confirm the core OLS findings, though with some attenuation of effect sizes as expected when spatial dependence is explicitly modeled. Importantly, the fundamental pattern of opposing relationships between traditional and digital social capital measures persists across the spatial specifications, reinforcing confidence in our primary findings about the differential roles of these social capital dimensions in regional economic vitality.

[7]Diagnostics for the spatial LM tests are presented in Table C1 in the appendix. These tests reveal highly significant spatial dependence across all three outcome variables, with SARMA test statistics ranging from 925.90 for employment change to 1,845.58 for population change (all p < 0.001).

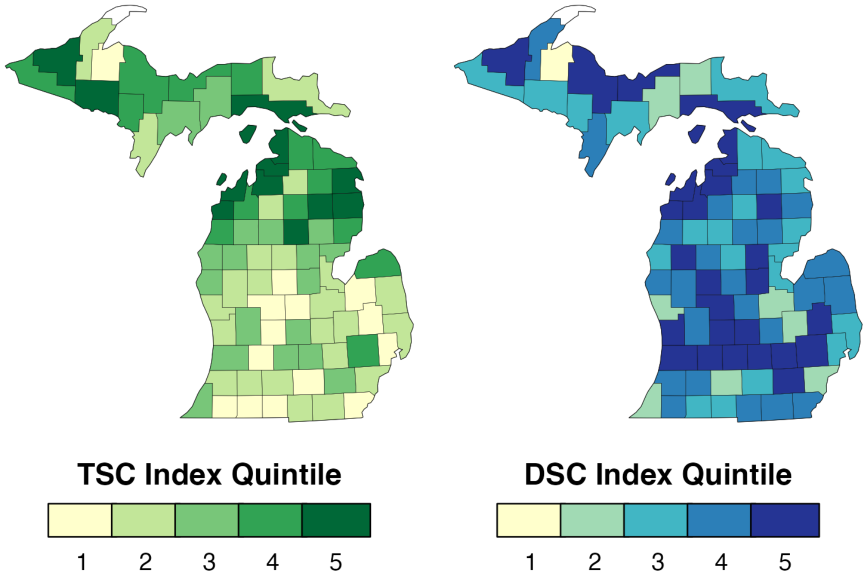


Figure 5: *TSC and DSC Comparison in Michigan*

6. Discussion & Conclusion

The weak correlation between traditional and digital social capital measures, along with their opposing relationships to economic outcomes, suggests that these approaches capture fundamentally different dimensions of social organization rather than alternative measurements of the same underlying phenomenon. Their divergent relationships with economic outcomes suggest distinct pathways to development, with implications that strike at the heart of community development practice.

Communities rich in traditional social capital tend to excel at maintaining economic stability and supporting existing residents through robust institutional networks. In contrast, those with robust digital social capital appear better positioned to attract new residents and businesses through broader connectivity. This distinction highlights that effective community development strategies should be tailored to a community's specific social capital profile, rather than adopting a one-size-fits-all approach. Rather than simply inventorying the amount of social capital, stakeholders should focus on the type of social capital present, recognizing, for instance, that the assets that preserve community character may differ substantially from those that stimulate economic growth.

Our exploratory analysis of traditional social capital over time identified a trend of positive growth with TSC increasing from 2002 to 2012 and again from 2012 to 2022. This upward trajectory contradicts expectations derived from conventional expectations such as Putnam's "Bowling Alone" thesis (2000), suggesting that community associational density and civic participation have collectively strengthened rather than declined.

The spatial dimensions of our exploratory analysis revealed that allocations of social capital are not uniform across the country, with persistent regional disparities in social capital that persist regardless of measurement approach. Regarding the urban-rural divide, our findings suggest that nonmetropolitan counties may hold an advantage in traditional social capital, as rural areas tend to exhibit stronger brick-and-mortar institutions and higher levels of civic engagement. Conversely, in metropolitan areas where traditional civic institutions may be less robust, residents might instead foster community ties and coordinate local activities through digital networks and platforms, effectively using online connectivity to fill gaps left by weaker brick-and-mortar organizations.

What might this mean in a practical sense? Using the state of Michigan as an illustrative case, the maps in Figure 5 highlight stark differences in the spatial distribution of both types of social capital. In rural parts of the state with stronger traditional social capital, residents might be more likely

Table 8: Summary of Social Capital Effects on Regional Outcomes (2017–2022)

Model / Variable	Employment	Population	Income
Traditional Social Capital	▼	▼	▲
Digital Social Capital	▲	▲	▼

Key:
▲: Statistically significant positive effect ($p < 0.05$)
▼: Statistically significant negative effect ($p < 0.05$)

to engage in community life through longstanding institutions that foster face-to-face interaction and collective action (Ulrich, 2010). Along the I-94 corridor, where digital networks are stronger but traditional institutions are weaker, residents in metropolitan Detroit, Lansing, and Kalamazoo might instead rely on digital platforms like Facebook groups or Nextdoor to coordinate neighborhood events, share information, and maintain social ties in the absence of strong traditional associations.

As summarized in Table 8, traditional social capital (TSC) is associated with higher income growth but lower employment and population growth, while digital social capital (DSC) correlates with higher employment and population growth but lower income growth. For policymakers and stakeholders considering social capital in community economic development, these findings stress that traditional and digital social capital exert distinct and sometimes opposing effects on key regional outcomes.

If a community's TSC is stronger, our research suggests that practitioners might be more effective if they focus on strategies that leverage stable institutional networks to support resident retention, preserve local character, and foster income growth. In contrast, if DSC is stronger, development efforts should emphasize growth, innovation, and attracting new residents or businesses by utilizing digital connectivity and online engagement. For communities with limited resources, tailoring local programs to match the dominant form of social capital (rather than applying a uniform approach) can maximize impact and avoid unintended trade-offs. Whether rooted in long-standing institutions or digital networks, aligning development strategies with the community's unique social capital profile offers a clearer path to realizing locally meaningful goals. In short, the most successful community development efforts will be those that start by asking: What kind of social capital do we have, and how can we use it to achieve the economic outcomes we value most?

6.1. Limitations & Future Directions

This study was limited by the lack of consistent, publicly available metrics that could be used to create a longitudinal (i.e., annual) panel of traditional and digital social capital at the county level. While this limitation did not prevent us from conducting exploratory correlation and descriptive multivariate analysis, it does prevent a deeper quasi-experimental analysis that might explore the causal linkages between social capital and community economic outcomes. Future research may incorporate a longitudinal analysis of digital social capital when such data becomes available.

A further limitation was the reliance on counties as the geographic unit of analysis. Counties and communities are not synonymous: a single county may encompass multiple distinct communities, while many communities extend across county boundaries. Although the DSC metrics adapted from Chetty et al. (2022b) were also available at the ZIP code and school district levels, the data required to replicate the Rupasingha et al. (2006) TSC index are not readily accessible at smaller geographic scales. Researchers with access to more granular data may be able to provide a more nuanced understanding of social capital; however, in general, there is no single geographic unit that can perfectly capture the complex and overlapping nature of community boundaries and social networks.

Future research should also focus on deepening our understanding of how social capital changes over time. For example, qualitative studies could provide more subtle descriptions of the mechanisms driving the distinct relationships we found between traditional and digital forms of social capital and their respective impacts on economic outcomes.

Such work could help clarify why these different types of social capital predict varying patterns of community development. Researchers can also investigate whether our results apply to other community outcomes beyond economic growth, such as local innovation or resilience.

6.2. Conclusion

While it may be true that we no longer live in a world where a community's social health can be gauged merely by tallying local bowling alleys and Rotary Clubs, it is also true that our social interactions have not migrated so completely to digital platforms as to be wholly quantifiable using online metrics of connectedness. As such, this study's central finding is that traditional and digital measures of social capital are complementary rather than equivalent in the 21st century. Moving forward, community development researchers and practitioners must adopt integrated measurement frameworks that capture both institutional civic engagement and digital network connectivity, tailoring strategies to the unique social capital profiles of communities. This more refined understanding enables a more effective response to community-specific challenges in an increasingly connected yet fragmented social environment.

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Appendices

Appendix A: TSC & DSC Scatterplot Outliers

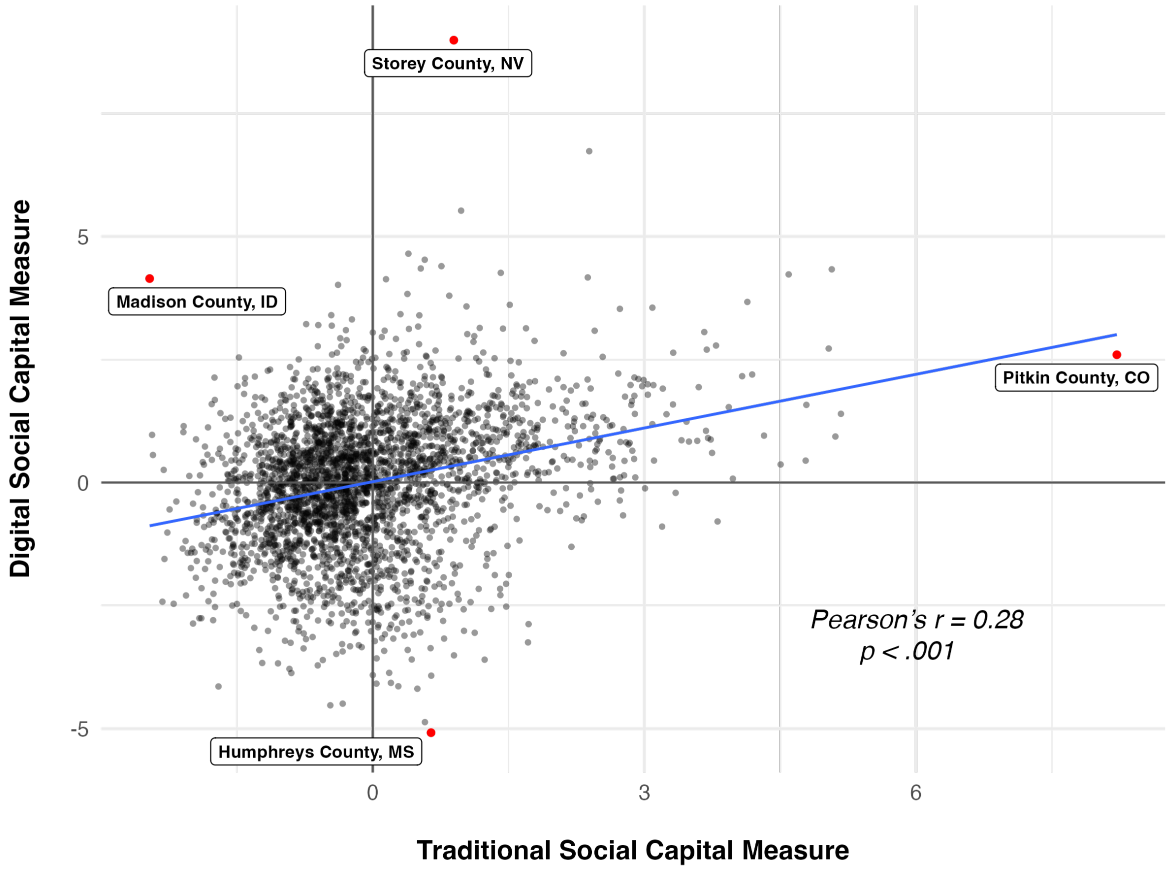

Figure A1: *Outliers Highlighted for Each Quadrant of TSC/DSC Scatterplot*

Appendix B: Combined Social Capital Hotspots

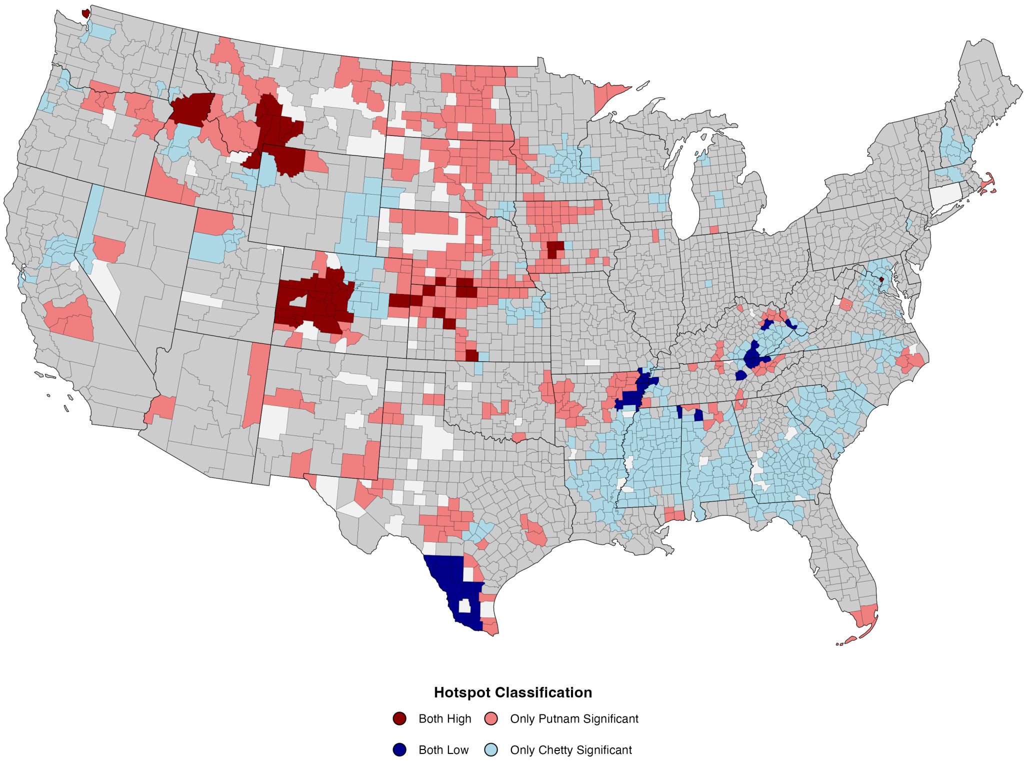

Figure B1: *Counties Significant for both Traditional and Digital Measures*

Appendix C: Spatial Dependence Diagnostics

Table C1: *Spatial Dependence Diagnostics: Lagrange Multiplier Tests for OLS Models*

Diagnostic Test	Statistic	DF	p-value
Population Change			
LM Error	1,814.91	1	<0.001
LM Lag	1,616.49	1	<0.001
Robust LM Error	229.09	1	<0.001
Robust LM Lag	30.67	1	<0.001
SARMA	1,845.58	2	<0.001
Employment Change			
LM Error	899.77	1	<0.001
LM Lag	897.20	1	<0.001
Robust LM Error	28.70	1	<0.001
Robust LM Lag	26.13	1	<0.001
SARMA	925.90	2	<0.001
Income Change			
LM Error	1,171.63	1	<0.001
LM Lag	1,177.72	1	<0.001
Robust LM Error	20.15	1	<0.001
Robust LM Lag	26.24	1	<0.001
SARMA	1,197.87	2	<0.001

Appendix D: Spatial Autoregressive Combined Models

Table D1: *Spatial Autoregressive Combined (SAC) Model: Population Change*

	TSC Only	DSC Only	Both
	(1)	(2)	(3)
Traditional Social Capital (TSC)	-0.011^{***}		-0.014^{***}
	(0.001)		(0.001)
Digital Social Capital (DSC)		0.008^{***}	0.013^{***}
		(0.001)	(0.001)
Log Population Density	-0.004^{***}	-0.001	-0.003^{*}
	(0.001)	(0.001)	(0.001)
Unemployment Rate	-0.004^{***}	-0.002^{***}	-0.003^{***}
	(0.000)	(0.000)	(0.001)
Age Dependency Ratio	0.127^{***}	0.071^{***}	0.128^{***}
	(0.010)	(0.009)	(0.010)
Industry Diversity	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)
Bachelor's Degree or Higher	0.113^{***}	-0.018	0.063^{***}
	(0.011)	(0.011)	(0.013)
Metropolitan County	0.014^{***}	0.013^{***}	0.012^{***}
	(0.002)	(0.002)	(0.002)
Census Division FE	Yes	Yes	Yes
Observations	2929	2929	2929
AIC (Linear model)	−9965.935	−10037.508	−10245.518
AIC (Spatial model)	−10992.332	−10931.516	−11151.285
LR test: statistic	1030.398	898.009	909.766
LR test: p-value	0.000	0.000	0.000

Table D2: *Spatial Autoregressive Combined (SAC) Model: Employment Change*

	TSC Only	DSC Only	Both
	(1)	(2)	(3)
Traditional Social Capital (TSC)	-0.009^{***}		-0.009^{***}
	(0.001)		(0.001)
Digital Social Capital (DSC)		0.005^{***}	0.005^{***}
		(0.001)	(0.001)
Log Population Density	0.000	0.003	0.000
	(0.001)	(0.001)	(0.001)
Unemployment Rate	-0.003^{***}	-0.002^{*}	-0.002^{*}
	(0.001)	(0.001)	(0.001)
Age Dependency Ratio	0.144^{***}	0.103^{***}	0.138^{***}
	(0.015)	(0.014)	(0.016)
Industry Diversity	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Bachelor's Degree or Higher	0.136^{***}	0.040^{*}	0.098^{***}
	(0.017)	(0.017)	(0.020)
Metropolitan County	0.023^{***}	0.023^{***}	0.022^{***}
	(0.003)	(0.003)	(0.003)
Census Division FE	Yes	Yes	Yes
Observations	2929	2929	2929
AIC (Linear model)	-7566.972	-7567.046	-7612.749
AIC (Spatial model)	-7963.864	-7943.928	-7983.995
LR test: statistic	400.892	380.882	375.246
LR test: p-value	0.000	0.000	0.000

Table D3: *Spatial Autoregressive Combined (SAC) Model: Income Change*

	TSC Only	DSC Only	Both
	(1)	(2)	(3)
Traditional Social Capital (TSC)	0.010^{***}		0.010^{***}
	(0.002)		(0.002)
Digital Social Capital (DSC)		-0.003	-0.003^{*}
		(0.002)	(0.002)
Log Population Density	-0.001	-0.005	-0.001
	(0.002)	(0.002)	(0.002)
Unemployment Rate	-0.004^{**}	-0.005^{***}	-0.004^{***}
	(0.001)	(0.001)	(0.001)
Age Dependency Ratio	0.022	0.066^{***}	0.025
	(0.019)	(0.018)	(0.019)
Industry Diversity	0.000^{**}	0.000^{**}	0.000^{***}
	(0.000)	(0.000)	(0.000)
Bachelor's Degree or Higher	0.041	0.111^{***}	0.063^{**}
	(0.022)	(0.023)	(0.024)
Metropolitan County	-0.003	-0.004	-0.002
	(0.003)	(0.003)	(0.003)
Census Division FE	Yes	Yes	Yes
Observations	2929	2929	2929
AIC (Linear model)	-6228.691	-6208.413	-6249.852
AIC (Spatial model)	-7102.751	-7073.090	-7104.666
LR test: statistic	878.060	868.677	858.814
LR test: p-value	0.000	0.000	0.000